

Nearest-neighbor field algorithm based on patchMatch for myocardial perfusion motion estimation/correction

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ABSTRACT

Deformation correction and recovery of dynamic magnetic resonance images (DMRI) with low complexity algorithms without compromising image quality is a challenging problem. We proposed a motion estimation deformation-correction compressive sensing (DC-CS) scheme to recover dynamic images from its undersampled measurements. We simplify the complex optimization problem into three sub-problems. The contributions of this research are: introducing a global search strategy instead of the DC registration step, guaranteeing a non-explicit motion estimation that avoids any spatial alignment or registration of the images, and lowering the computational cost to the minimum by using PatchMatch (PM). The simulation result shows that the PM algorithm accelerates the recovery time without losing the quality in comparison with the DC algorithm.

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1. INTRODUCTION

Dynamic magnetic resonance imaging (DMRI) data is naturally stacked in two dimensions and involves entities that are evolving in time. Magnetic resonance imaging (MRI) is very important in many clinical examinations including vocal tract imaging, brain, cardiovascular, abdominal, and pulmonary [1], [2]. Any voluntary or involuntary motion generated by muscles or other physiological movements during the imaging procedure adds to the complexity of MRI image manipulation. Therefore, and because of the slow acquisition nature of DMRI, it usually compromises the quality of output images. In other words, for accurate quantification of myocardial perfusion in MRI data, it is essential to have an extended slice, a suitable spatio-temporal resolution, coverage, and a high signal to noise ratio (SNR) [3], [4].

To overcome aforementioned challenges, including parallel imaging, and their combination with k-t spatio-temporal models, many schemes were proposed in the literature [5]–[10]. However, these schemes are suitable for specific applications and tradeoff the quality with the complexity cost. Machine learning based schemes were proposed to solve the problem of motion estimation and deformation correction [11]–[14]. However, it does offer substantial evidence for the clinical significance of such a solution in the sense of motion estimation below the sampling rate.

For some real-life applications, including medical imaging [15], the Nyquist rate is not applicable or viable, or even physically possible to build such a device, an explosive growth in the signal processing approach of compressed sensing (CS) for perfectly reconstructing data that are significantly sampled below the Nyquist rate [16]. Since the reconstruction of medical images required vectorization or matricization of the underlying data [17], CS is directly applied to multidimensional structure of dynamic MRI data. Dwivedi *et al.* [18] proposes a learning method using a tensor dictionary under an orthonormal constraint to

reconstruct DMRI as an alternates sparse coding algorithm. Lingala *et al.* [19] introduces a novel CS algorithm for jointly deformation correctness accelerated dynamic MRI, with a capability of handling a wide range of compactness/sparsity. Quantification feasibility for a whole-heart, non-electrocardiograph (ECG)-gated, cardiac-phase-resolved myocardial perfusion MRI framework and free-breathing was developed and tested in [20] using the CS framework. These methods have the ability to recover the data successfully for minimal inter frame motion, but they are sensitive to large inter frame motion. Lakshminarayana and Sarvagya [21] used CS in medical images with hybrid compression methods.

In this piece of work, a novel estimation/correction approach were propose to reconstruct dynamic MRI images from under sampled measurements. The dynamic images and inter frame motion were jointly estimated. We used the variable splitting to decouple the main problem into three simpler sub-problems. Most importantly, we lowered the complexity cost of the deformation registration scheme (step), which registers each frame in the dataset to its correspondence step by step, through using patchMatch (PM) process instead. Finally, we illustrate the utility of our proposed framework in the context of myocardial perfusion.

We organized the paper as follows: section 2 discusses the research method including the deformation-corrected CS framework and proposed algorithm. In section 3 we demonstrate the use of the proposed framework. Section 4 concludes our results.

2. RESEARCH METHOD

In this framework, it has been proposed a combining deformation-correction compressive sensing (DC-CS) approach using a global search based on PM novel random search algorithm. Under the presumption of exploiting redundant in similar patches across different subjects, it has been used NNF in association with the DC-CS approach for MRI image recovering.

2.1. DC-CS for dynamic magnetic resonance imaging

Inter frame motion recovery scheme can be modelled as low rank matrix problem which can be perfectly solved using compress sensing techniques. DC-CS minimizes the sensitivity of compressed data by estimating the dynamic images jointly with the inter frame motion. It was presumed to have a compact representation of the deformation corrected signal rather than the original signal. Similarly, we simplify the under-discussion problem using variable splitting into three smaller problems including a shrinkage-based denoising step, a quadratic optimization step, and deformable registration step. Also, in order to utilize the advantage of low rank structure in the construction, we considered various use of compactness priors including temporal finite difference domain, sparsity in the temporal Fourier domain, and nuclear norm penalty.

2.2. Problem formulation

The ultimate object of our framework is to recover the dynamic dataset $f(x, t)$ from it's under sampled Fourier noisy measures $b(k_j, t_j)$ where x denotes the spatial variable and t refers to time. Also, we would like to simulate the result using complexity low-cost algorithm. The dynamic MRI measurement process can be modeled in vector space as follows (1):

$$b = \Lambda(f) + n \quad (1)$$

where Λ is fourier transform evaluating operator from the sampling location in the set $(k_j, t_j), j = 1 \dots s - 1$. Lingala *et al.* [19] proposes a deformation corrected dataset to overcome the limitation associated with dynamic MIR deformation correctness, Γ_θ . It was assumed f to be compact-sparse and considerably structured.

In this work we consider simultaneously recovery of the deformation parameters $\Phi(x, t)$ and the dynamic images $f(x, t)$ from under sampled data $b(k, t)$ using the following general minimization scheme as (2):

$$\{f^* \theta^*\} = \min_{f, \theta} \|\Lambda(f) - b\|_2^2 + \lambda \Phi(\Gamma_\theta, f) \quad \text{such that } \theta \in \Theta \quad (2)$$

Here Λ is the fourier sampling operator, Γ_θ is image operator for non-rigid warping; $\theta(f, t)$ is deformation parameters which represents pixel wise displacements due to motion. This parameter is estimated from the under sampled data. The proposed scheme also yields $\Gamma_{\theta(f, t)} \cdot f$ that is version of f , to represent the deformation corrected, as a by-product. $\Phi(u)$ is an arbitrary prior to exploit the redundancy in the data and finally Θ is the set of coefficients that represent the deformation field like B-spline. The authors used a

variable splitting approach to decouple the original problem to simpler sub-problems. An auxiliary variable g was introduced to split the prior from the deformation term which enables formulating the problem using the following constraints as (3):

$$\{f, \theta^*\} = \min_{f, \theta, g} \left\| \Lambda(f) - b \right\|_2^2 + \lambda \Phi(g) \quad \text{such that } \Gamma_{\theta}, f = g, \theta \in \Theta \quad (3)$$

Figures 1(a)-(f) shows the DC algorithm, as a demonstration in the context of MRI myocardial perfusion. Hence, we can show some results on prospectively and retrospectively undersampled nuclear perfusion imaging (MPI) using radial trajectory. DC-CS reconstructions shows less motion artefacts and temporal blurring comparing to other CS schemes. Even though DC shows some promising results but still got some drawbacks. Some downsides of the algorithms are higher computational complexity, explicit motion compensation, slow running (mainly because of the deformation step, demon's algorithm), high memory demand and didn't use different choices of sampling patterns. To alleviate the drawback of the DC algorithm with confronted problem, we will use PM scheme.

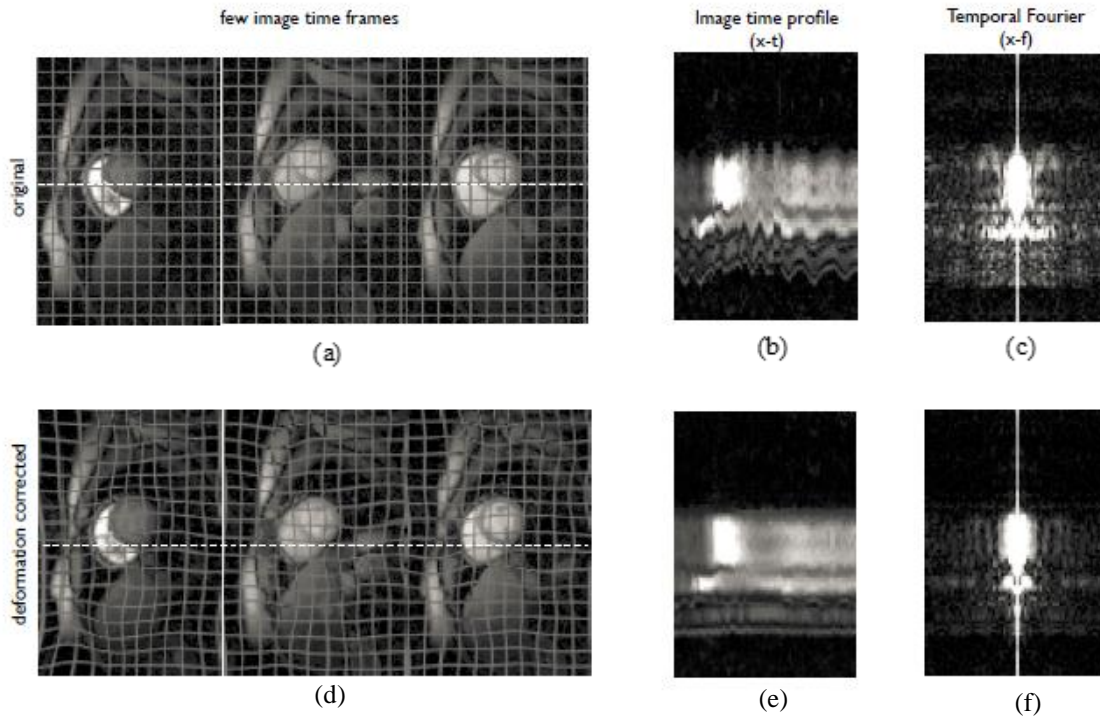


Figure 1. Free breathing multi-parametric MRI (MPMRI) with and without deformation correction (a) dynamic myocardial perfusion MRI frames, (b) the rippled time profile of the original datasets along the white dotted lines on the frames because of breathing, (c) temporal Fourier domain representation of the original dataset which shows the temporal harmonics corresponding to the motion are compensated in (f), (d) the deformed-corrected version of (a), (e) the free of ripples time profile of the deformed image along the white dotted lines on the frames, and (f) temporal Fourier domain representation of the deformation correction dataset which shows sparse representation

The registration was, performed on the free breathing dataset itself. By using the demon's registration algorithm, starting from the second frame, the deformations were found by matching the n -th frame in the moving, sequence to the $(n+1)$ -th of the deformed scene. Solving the optimization problem by relaxing the unconstrained problem yields (4):

$$\{f, \theta\}^* = \min_{f, \theta, g} \left\| \Lambda(f) - b \right\|_2^2 + \lambda \left(\Phi(g) + \frac{b}{2} \left\| \Gamma_{\theta}, f - g \right\|_2^2 \right) \quad \text{such that } \theta \in \Theta \quad (4)$$

Beta is the penalty parameter enforces the constraint. Using the iterative minimization scheme to solve the problem above by solving one variable and fixing the rest. They reiterate the three sub-problems until they converge.

- g sub-problem (spatio-temporal denoising/dealiasing to minimize residual motion as (5)-(7):

$$g^* = \min_g \frac{2}{\omega} \Phi(g) + \|\Gamma_{\theta,} f - g\|_2^2, \text{ where } q = \Gamma_{\theta,} f \quad (5)$$

$$\hat{g} = \min_g \frac{2}{\omega} \|\hat{g}\|_{l_1} + \|\hat{q} - \hat{g}\|_2^2 \quad (6)$$

$$g = \frac{\mathcal{F}_t(q)}{|\mathcal{F}_t(q)|} \left(|\mathcal{F}_t(q)| - \frac{2}{\gamma\omega} \right) \quad (7)$$

- f sub-problem (reconstruction update) as (8):

$$\min_f \|\Lambda(f) - b\|_2^2 + \frac{\gamma\omega}{2} \|\Gamma_{\theta,} f - g\|_2^2 \quad (8)$$

- Theta sub-problem (motion estimation) as (9):

$$\min_{\theta} \|\Gamma_{\theta,} f - g\|_2^2 \quad (9)$$

The dynamic $f(x, t)$ is registered frame by frame with a reference scene $g(x, t)$. Here, an iterative demon's algorithm was used to approximate the registration subproblem. As demon's is an iterative algorithm, the displacement field parameter $\theta(x, t_j)$ is updated in each iteration j by adding a force field.

Factor $u_n, \theta_{n+1} = \theta_n + u_n$, where u_n evaluated in the previous iteration ($n - th$ iteration). The force field is derived from intensity differences in the reference and target images. The risk of converging into a local minimum is still exist, therefore; the author employs continuation strategies to minimize its risk initializing beta parameter with very low values and increase it gradually. To speed up the convergence of the algorithm and to reduce local minima effects, the demon's implementation recommends a continuation on a force strength parameter. The resulting algorithm decreases the presence of local minima convergence through employing efficient continuation strategies. DC-CS considers a deformable registration scheme that registers the frames from the existing dataset to their corresponding.

2.3. PatchMatch technique for structural image editing

The work in [22] considers one of the landmarks for all time in image editing for its interactive ability of photo manipulation using fast randomize algorithm. The key strengthen of the framework is its new nearest-neighbour field (NNF) search algorithm which uses random sampling to find some good patch matches which quickly propagate to the surrounding areas through the cohesive nature of the imagery. The previous NNF algorithms attain high synthesis quality of patch optimization, but with a trade-off with the complexity which the bottleneck of such algorithm. In contrast, the technique in [22] not only achieves high quality results, but also provides almost real time photo editing tools for image application including image retargeting, completion, and reshuffling.

Most of the other algorithms which try to accomplish image reconstruction look in the image for regions that are like the one that was removed and borrow some information to fill out the process. Unlike these algorithms, when we are trying to do another lookup process, our algorithm does not restart the patch matching process. However, when good correspondence is found, it just searches nearby because that is where we can find the most useful information. The main idea here is that exploiting the local coherence in the synthesis process, speeds up the filling process through minimizing the search space to the neighbours of the patch local location. We borrow the coherence propagation assumption of our algorithm from the work in the [23].

In the context of the image editing application, our NNF algorithm, which is illustrated in Figure 2, has three phases: i) initially, patches possess random assignments; ii) the blue patch checks above/green and left/red neighbours to check whether there is a possible improvement to the blue mapping, and propagating a possible good match; and iii) the patch randomly searches the concentric neighbourhoods for improvements. In other words, a random offset (sometimes prior information) will be filling the NNF to apply an iterative update process. Adjacent pixels are occupied by good patch offsets. PM can determine an approximate 'nearest neighbour' match that could conceivably replace a given patch in the image. Once a reasonable match is found, it tries to improve this patch by randomly searching for better matches around the target position.

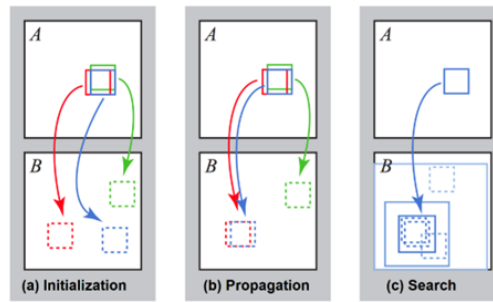


Figure 2. Scheme phases using a randomized approximation algorithm [23]

2.4. Proposed patchMatch for DC-CS scheme magnetic resonance imaging recovery

One of the main contributions of this work is introducing a global search strategy instead of the DC registration step, guaranteeing a non-explicit motion estimation that avoids any spatial alignment or registration of the images; in addition to use PM. Scheme to decrease the computational cost to the minimum. We propose a framework to combine the DC-CS approach using a global search based on the PM algorithm. We assume that information redundancy in similar patches across different subjects can be exploited. The basic patch match algorithm allows for the best matches between a source and target image to be found quickly. Most importantly we can change the slow and complex registration step by using the patch-based algorithm to implicitly estimate motion and do image reconstruction.

3. RESULTS AND DISCUSSION

The main reason behind thinking that our proposed scheme can be utilized in the image recon is that this patch-based method uses NNF which is good for motion estimation and the randomized search followed by propagation is not just fast, but easier to implement smoothness enforcement so we make sure the computational efficiency is kept lower. The basic patch match algorithm allows for the best matches between a source and target image to be found quickly. Most importantly we can change the slow and complex registration step by step using the patch-based algorithm to implicitly estimate motion and do image reconstruction. We did the simulation in Figure 3 with and without using the propagation step. We found that the result using the propagation step is pretty smooth and converges even better.

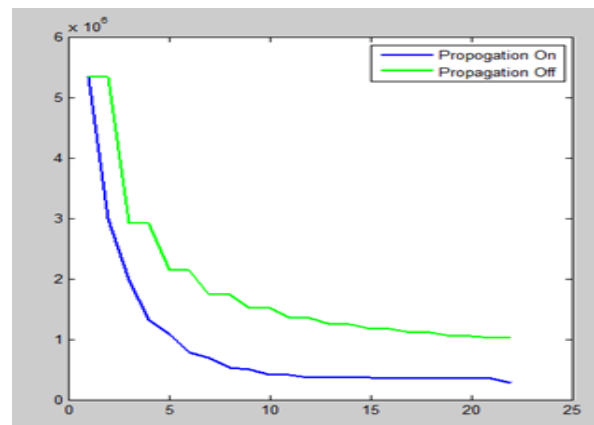


Figure 3. Error with (smooth) and without (zigzag) using propagation step

Figures 4 shows the implementation of PM which is done in C++ with a MEX interface to MATLAB. The starting points for them were chosen to be zeros and the neighborhood size was set of 20. 5 patches searches are involved and with a size of 5*5 each, thus we may recover five images from the original image. We have done the experiments using 256*256 vase image and 190*90 MPI. One observation is that PM preserves the edges well and gives good results. The 1st image in both figures always looks the best as it

is simply the translational version of the patches of the original image while the rest four images are obtained from the four neighboring patches within the search vicinity.

As PM breaks down an image into a series of small, overlapping rectangles of fixed size; it replaces the wrapping operator in DC by this scheme. More specifically, we replace the forward operator by 2nd neighbourhood PM and the backward one as the 1st neighbourhood which is simply the translated version of the image. We can also save time by doing PM only once by saving the image as an array of indices before applying the PM so we retrieve it easily by applying the inverse wrapping operator. By doing so we can make sure that the patches capture the motion in the frames without any complicated or explicit motion estimation.

Figure 5 shows one frame of the original image and the recon using the PM recovered from an acceleration factor of 5 using the radial undersampling operator. The shrinkage and f calculation steps were kept as they are in DC. We can see that the recovered image is almost an artefact-free and crispy. Minimizing the input and output number of iterations set in the DC algorithm might speed up the whole process. It is worth to mention that there are many other algorithms that can be tried to use which might improve the quality and the complexity of the work. We can also collaborate this algorithm with a neural network which can be a future improvement over this work [24]–[27].

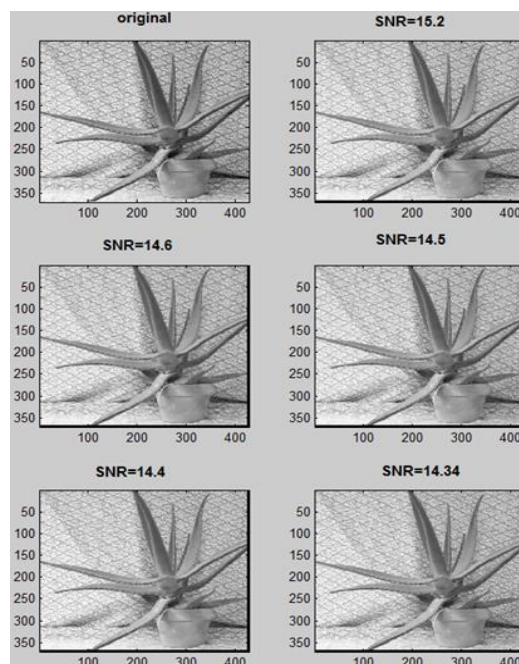


Figure 4. PM scheme for different SNR

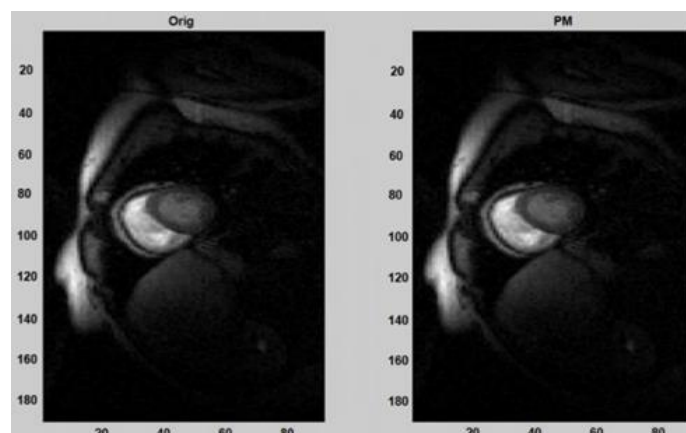


Figure 5. One frame of the original image and the recon using the PM recovered from acceleration factor of 5 using radial undersampling operator

4. CONCLUSION

In this framework, a novel estimation/correction approach was proposed for dynamic MRI image reconstruction from its under sampled measurements. The dynamic images and inter frame motion were jointly estimated. Also, we proposed a PM algorithm to be used instead of DC algorithms which has a high complexity that is the main challenge of data reconstruction. We used a global search strategy instead of the DC registration step to guaranteeing a non-explicit motion estimation that avoids any spatial alignment or registration of the images. One of the limitations we have faced is that the PM algorithm accepts only real-valued images that we are planning to address in the future.




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